

# **INTENSITY BASED IMAGE REGISTRATION OF SATELLITE IMAGES USING EVOLUTIONARY TECHNIQUES**

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF  
THE REQUIREMENTS FOR THE DEGREE OF

**Master of Technology**

in

**Electronic Systems and Communication**

by

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Department of Electrical Engineering  
National Institute of Technology  
Rourkela, Orissa, India  
May 2014

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**Under the guidance of  
Prof. Dipti Patra**



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May 2014



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# CERTIFICATE

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This is to certify that the thesis entitled “**Intensity Based Satellite Image Registration Using Evolutionary Techniques**”, submitted by **Guguloth Uma (Roll. No. 212EE1217)**, in partial fulfillment of the requirements for the award of **Master of Technology in Electrical Engineering** during session 2012-2014 at National Institute of Technology, Rourkela is a bonafide record of research work carried out by her under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any Degree or Diploma.

**Place: Rourkela**

INSTITUTE OF TECHNOLOGY  
ROURKELA

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**Dept. of Electrical Engineering**  
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# ABSTRACT

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Image registration is the fundamental image processing technique to determine geometrical transformation that gives the most accurate match between reference and floating images. Its main aim is to align two images. Satellite images to be fused for numerous applications must be registered before use. The main challenges in satellite image registration are finding out the optimum transformation parameters. Here in this work the non-alignment parameters are considered to be rigid and affine transformation. An intensity based satellite image registration technique is being used to register the floating image to the native co-ordinate system where the normalized mutual information (NMI) is taken as the similarity metric for optimizing and updating transform parameters. Because of no assumptions are made regarding the nature of the relationship between the image intensities in both modalities NMI is very general and powerful and can be applied automatically without prior segmentation on a large variety of data and as well works better for overlapped images as compared to mutual information(MI). In order to get maximum accuracy of registration the NMI is optimized using Genetic algorithm, particle swarm optimization and hybrid GA-PSO. The random initialization and computational complexity makes GA oppressive, whereas weak local search ability with a premature convergence is the main drawback of PSO. Hybrid GA-PSO makes a trade-off between the local and global search in order to achieve a better balance between convergence speed and computational complexity. The above registration algorithm is being validated with several satellite data sets. The hybrid GA-PSO outperforms in terms of optimized NMI value and percentage of mis-registration error.

# CHAPTER 1

## INTRODUCTION

---

### 1.1 Image Registration

The geometric registration of images is a fundamental task in many applications in remote sensing image processing. Image registration is the fundamental image processing technique to determine geometrical transformation that gives the most accurate match between reference and floating images [1]. Image registration is a process of establishing the best correspondences between the images of the same scene taken at different times (multi-temporal) or taken at different view-points(multi-view) or by different sensors(multi-modal).The main reason for non-alignment of images of same scene is due to various reasons, i.e. calibration issues, setup errors of scanning machine, different scan geometry like slice position, orientation, magnification, thickness of different sensors and may be due to relative motion between the camera and object planes. Hence the non-aligned images need registration before any other image processing steps. The basic aim of image registration is to find out a geometric transformation model which would align the floating image with respect to the reference co-ordinate system. The goal is to establish the best correspondence between two images and to determine a geometric transformation that aligns two images: the reference and sensed image.

Assume two images  $I_1(x, y)$  and  $I_2(x, y)$  are two images same but taken from different sensors. The images are 2-dimensional and have some intensity value. The image registration problem is to find the mapping between two images  $I_1$  and  $I_2$  that gives the best correspondence.

$$I_2(x,y) = I_1(f(x,y))$$

$f: I_1(x,y) \rightarrow I_2(x,y)$  performs the mapping between images .

Approximation to  $f$  can be constructed by some transformation: rigid, affine.

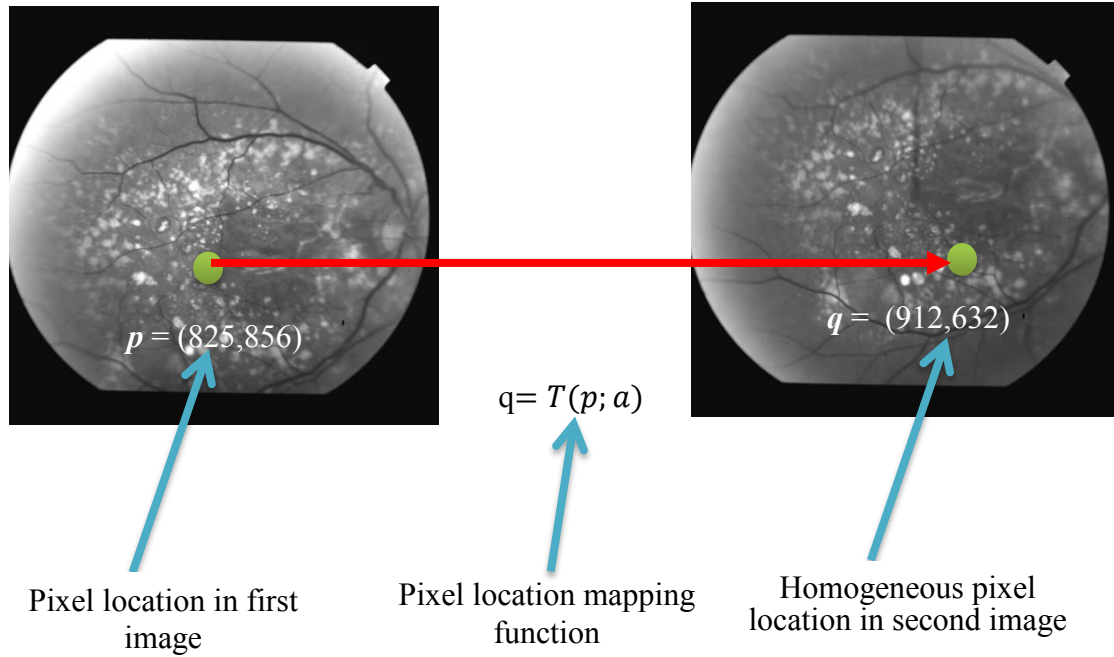


Figure 1.1: Basic image registration

In case of satellites the data is taken from different sensors, different viewpoints, and at different time instances. The task of satellite imaging in registration algorithms can be classified as surface based, landmark based. Frame-based registration is accurate, but complex, any external point landmark-based depends on the accurate corresponding landmarks in all images of the same scene. Surface segmentation algorithms are usually highly application and data dependent and in many of the cases surfaces are not easily identified. Optimization of a functional measure of the similarity of corresponding voxel pairs for some feature is the basic idea behind Voxel-based (VSB) registration methods. Feature calculation is simple is the advantage of VSB methods or even absent when only grey-values are used, so the accuracy of these methods is not limited. Existing image registration techniques classified into two well-known categories: feature-based and intensity-based methods. Extraction of common features in reference and floating images are the main approach used in a feature-based method. Extraction of selected features (control points) to the geo-stationary accuracy plays a vital role in feature based approach.

In feature based method pre-processing techniques, feature selection, feature correspondence and resampling techniques are applied. Pre-processing method does scale adjustment, noise removal and segmentation. In feature selection between two images, correspondence is established and it

uses lines, curves, templates, regions and patches. In contrast, limitation of intensity-based image registration techniques are free because rather compare intensity patterns in images they do not deal with the identification of geometrical landmarks. In this the mapping transformation is determined directly from the image intensities of the two images without prior knowledge. In intensity based registration Feature space, search space, search strategy, similarity measure are 4 important considerations. In feature space information is extracted from type of domain and Search space is the class of potential transformations used to align the images such as rigid body, elastic etc. Similarity metric is an indicator how closely the intensity values of two images are matched and here cross-correlation, the sum of squared intensity difference, mutual information, normalized mutual information are some of the similarity measures.

## 1.2 Classification of Registration Methods

Registration techniques are classified or categorized based on image dimensionality, geometrical transformation, basis of registration, optimization, and degree of interaction. Image dimensionality explains to the 2D, 3D geometrical number of the image spaces involved in registration problem. In this work, implementation of two dimensional satellite images or remote sensing images has been used [2]. In medical applications three dimensional image sets are used for registration problem.

- Geometrical transformation is based on domain of transformation and nature of transformation. These domains refer to the mathematical form of the geometrical mapping used to align points from one image to the other.
- Degree of interaction mentions that the control applied over the registration algorithm. And it consists of the initialization of parameters throughout the registration process. The optimization procedure is the method which includes degree of interaction.

Image registration can be divided according to the manner of the image acquisition as following:

**Multi-view analysis:** Images are acquired from different angles/viewpoints and the aim is to gain larger view representation of the registered image.

**Multi-temporal analysis:** Images are acquired from at different times, and under different conditions and the aim is to find and evaluate changes in the scene which appeared between the consecutive images acquisitions.

**Multi-modal analysis:** Images are attained from altered sensors and the aim is to incorporate the information acquired from different sources and detailed scene representation.

- Template registration techniques are used to find a match for a reference pattern in an image and in this process templates are selected from reference and target images, and it does mapping between these two images.

### 1.3 Image Registration of Satellite Images

Image registration of remote sensing aims is to integrating information from different characteristics of sensors i.e. panchromatic images, for better spatial resolution, color/multispectral images. Challenges in remote Sensing image registration are the conditions of data acquisition, size of the data, lack of a known image model, and lack of well-distributed control points [4]. Navigation error and atmospheric and cloud interactions has also an important impact on the quality of image registration.

### 1.4 Motivation

With the availability of space multi sensor setting, satellite imaging has a vital number of applications such as planning and analysis of land use, validation of satellite navigation data and mostly in the area of image fusion. Based on type of modality the registration process has to be done. The motivation of intensity based satellite image registration arises from the need to combine or compare the images of the same scene taken from different sensors primarily depends on the similarity measure, the used optimization technique to minimize or maximize the similarity measure and most importantly depends upon the transformations followed but not upon the features or control points common in both the images which is a difficult task to perform. In this thesis rigid, affine transformations are considered as registration problem. Normalized mutual information based rigid image registration has done by using genetic algorithm, particle swarm optimization methods, GA is completely random based technique and it's complex to implement. PSO algorithm converges prematurely and weak local search ability

is the main drawback of PSO. So in order to overcome the drawbacks of GA, PSO algorithms, hybrid GA-PSO algorithm have been proposed. It gives the maximum normalized mutual information values than GA, PSO algorithms and it achieves the better balance between local search and global search techniques

## **1.5 Literature survey**

The following are the literature reviews done on intensity based image registration and its evolutionary techniques [2].

**Brown [1]** has given a widespread survey on image registration methods. He categorized them into feature based and intensity based techniques. In this paper intensity based techniques are used.

**Barbara Zitova and Jan Flusser [2]** proposed a comprehensive survey of image registration methods. The image registration techniques are classified as area based methods and feature based methods.

**Ardeshir, Goshtasby [3]** “Registration of images with geometric distortions. Image registration methods are classified based on geometric distortions.

**Eastman R. D., Le Moigne J. & Netanyahu N. S.[4]** presented different research issues in the area of image registration.

**Mark Jenkinson, Stephen Smith [5]** presented a robust affine registration of a global optimization method.

**Rakesh Singhai and Jyoti Singhai [6]** studied Registration of satellite imagery using genetic algorithm and implementation of genetic algorithm, its convergence criterion and complexities involved in the genetic algorithm are mentioned.

**Chen-Lun ōin, Rui Xu and Yen-Wei [7]** presented problems, implementation of 2D non-rigid image registration using Particle Swarm Optimization. In PSO, the convergence is slow and is trapped in local optimum.

**S. K. Makrogiannis, N. G. Bourbakis, S. Borek[12]** proposed Automatic Registration of Aerial Images using Optimization Scheme.

**Mohammed Yagouni[13]** proposed metaheuristics for Optimizing Satellite Image Registration,. **Hartmann, K.G. Mehrotra, C.L. Gerberich and C.R.P.; P.K. Varshney, [14]** Presented on information theory Applications to the construction of efficient decision trees.

**P. Viola and W.M. Wells III, F. Maes, A. Collignon, D. Vandermeulen, G. Marchal, and P Suetens[14]** Presented on maximization of mutual information and Alignment of maximization of mutual information using Multimodality image registration.

## **1.6 Applications of Image Registration**

Image registration has many applications in the areas of remote sensing, medical images, computer vision, and pattern recognition [1].

### **1.6.1 Remote Sensing Applications**

In remote sensing applications image registration is an important operation, that basically does the identification of control points in the images. The increased volume of satellite images has strengthens the need for automatic image registration methods.



Figure 1.2: Remote sensing images

### **1.6.2 Medical Image Applications**

In radiotherapy planning, computed tomography (CT) data dose calculation is done, while tumour outlining is usually better performs in the corresponding magnetic resonance (MR) scan and for brain function analysis, MR images provide anatomical information while functional information will be obtained from positron emission tomography (PET) images and multimodality images core to improve diagnosis, surgical planning, further precise radiation therapy and few other medical aids by using registering images.

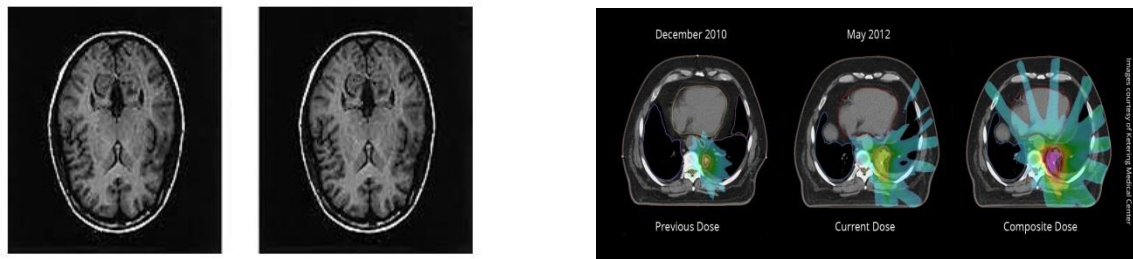


Figure 1.3: Bio-medical images

### 1.6.3 Computer Vision

Computer vision has found variety of applications in image registration. Target template matches with real time images, quality inspection automatically, (shape recovery) shape from stereo, change detection for motion tracking, security monitoring. For image mosaicking and motion detection on images of real scenes image registration plays vital role.

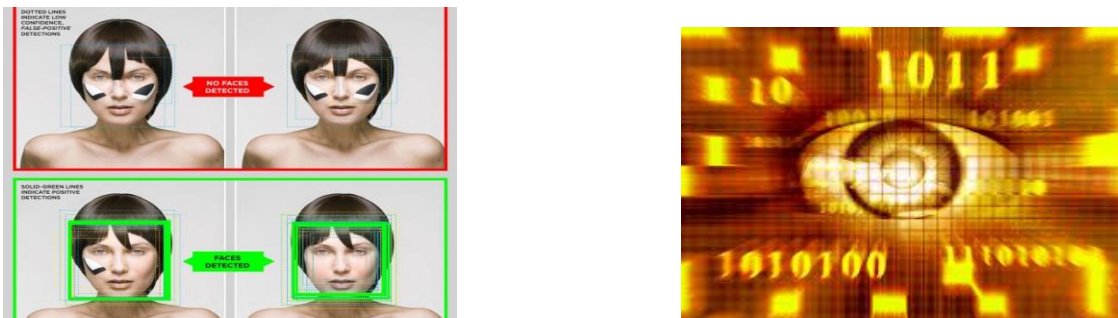


Figure 1.4: computer vision images



### 1.6.4 Pattern Recognition

Pattern recognition is primarily concerned with the classification and description of measurements taken from physical processes. The decision theoretic approach and syntactic approach are used to solve the problems of pattern recognition are used in mathematical models. Image registration plays an important role in alignment of object model instance and image of unknown object (segmentation).



Figure 1.5: Pattern Recognition Images

### 1.7 Objective of the Thesis

The objectives of the thesis are described as follows.

1. Normalized mutual information based rigid image registration and optimization of corresponding transformation parameters using genetic algorithm (GA), particle swarm optimization (PSO).
2. Normalized mutual information based affine image registration and optimization of corresponding transformation parameters using genetic algorithm (GA), particle swarm optimization (PSO).
3. Development of new algorithm hybridizing the notion of both GA and PSO for optimization of transformation parameters of rigid and affine image registration.
4. Performance comparison of image registration methods of satellite images using GA, PSO, and proposed hybrid GA-PSO algorithm.

## 1.8 Thesis Contributions

In this dissertation, the contributions in the area of normalized mutual information based image registration both for rigid and affine transformations using evolutionary techniques are described as follows. Namely, this research has:

- Implemented and investigated the effectiveness of Genetic Algorithm for optimization of registration transformation parameters.
- Implemented and investigated the effectiveness of PSO for optimization of registration transformation parameters.
- Developed, implemented and investigated the effectiveness of proposed hybrid GA-PSO algorithm for optimization of registration transformation parameters.
- All algorithms are validated with satellite images both in rigid and affine registration mode.
- Performance comparison of GA, PSO and proposed hybrid GA-PSO shows that the proposed algorithm outperforms the other two in terms of registration accuracy.

# CHAPTER2

## BACKGROUND THEORY

---

### 2.1 Block Diagram of Image Registration

The required steps involved in image registration are shown in Figure 2.1. For registration process two images required they are R and F are the two images, where R is the reference image and F is the floating image. In this process floating image should be matched with the reference image by applying the transformation function  $T(p, \mu)$ , the set of transformation parameter  $\mu$  has to be determined.

The correspondence between the sensed image and the reference image is established using similarity measures such as

- Absolute difference
- SSD (Sum of Squared Difference)
- Correlation Coefficient
- Mutual Information / Normalized Mutual Information.

The best transformation parameters give the maximum similarity metric which is normalized mutual information in this work. The parameters of the mapping functions are computed by correspondence. The model of deformation defines the mode of transformation between the reference image and the transformed image: Rigid body, affine, and elastic transformations are common in registration. The best transformation parameters give the maximum similarity metric which is normalized mutual information. In this process, optimization algorithm searches the best transformation parameters in the given space to find the best values for the maximum similarity metric. The image registration problem can be formulated as an optimization problem.

$$\hat{\mu} = \arg \max_{\mu} NMI (R(r), F(T(p; \mu))) \quad (2.1)$$

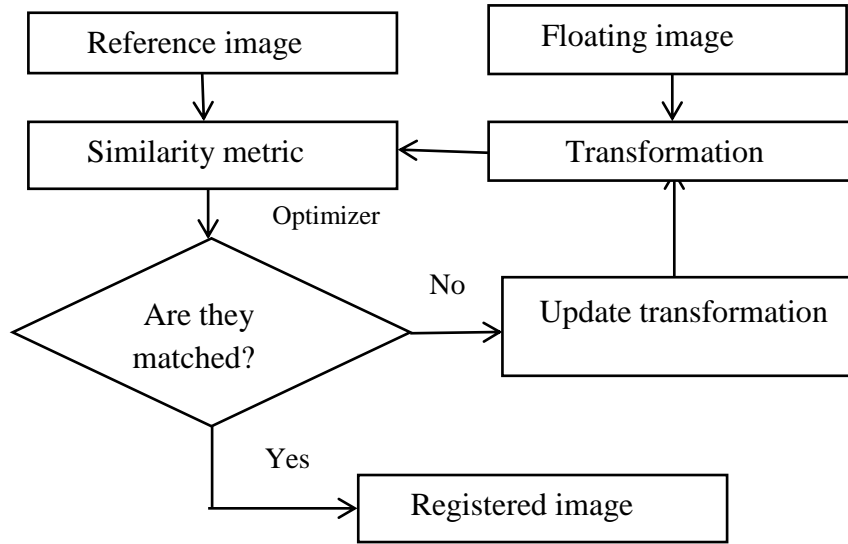


Figure 2.1: Block Diagram of Image Registration Method

The transformed floating image  $F(T(p;\mu))$  is aligned with the reference image  $R$  for alignment problem, we need the set of transformation parameters  $\mu$  that maximizes the image cost function i.e. the similarity measure. In this equation,  $\hat{\mu}$  is the best transformation and  $T$  is showing the transformation and its parameters for simplicity. The objective of the optimization strategy is to find the best transformation mode based upon a given image similarity criterion as well as to a search of the space defined by deformations. Finding the “best” or “optimum” value of an objective (cost) function (transformation parameters) is the main aim.

## 2.2 Similarity Measure for Image Registration

To register images, similarity measures are used by finding out the best (similarity) match between floating image and transformed versions of the reference image. Similarity measure shows how closely the intensity values of features of two images match. Correlation, normalized Cross-correlation, statistical correlation, match filters, phase-correlation, sum of absolute differences, root mean square, masked correlation, mutual information and normalized mutual information are the techniques of similarity measure. In this work normalized mutual information as a similarity metric has been implemented [21].

Normalized mutual information concept comes from the basics for the field of information theory and it is derived from the mathematical models. Information theory was developed in 1948 by Shannon to find fundamental limits on signal processing operations and it is also called as Shannon's information theory. It has many applications in the field of cryptography, statistical inference, quantum computing and data analysis etc[16].

Information is measured through entropy, joint entropy, conditional entropy, mutual information. Entropy can be defined as the average number of bits needed to communicate one symbol in a message. Entropy measures the amount of uncertainty of the random variable. Entropy is main building blocks of information theory and it is measured in the form of bits, it is denoted with H.

Entropy of X, denoted by H(X) is given by

$$H(X) = -E_X[\log_2(P(X))]$$

(or)

$$H(X) = -\sum p_i \log_2 p_i$$

Where, X is a random variable

$p(x)$  be the probability density of x

Joint entropy can be defined as how much amount of information both the images have combined and there are two variables in joint entropy. Mathematically, it can be expressed as

$$H(X, Y) = -E_{XY}[\log_2(P(X, Y))] \quad (2.2)$$

Mutual information (MI) concept comes from information theory for measuring the statistical dependence between two random variables. When two images are perfectly matched then it gives the maximum similarity metric. Mutual information measure can be described in several ways. Mathematically it can be expressed as

$$MI(X, Y) = H(X) + H(Y) - H(X, Y) \quad (2.3)$$

$$H(X) = -\sum p_i \log_2 p_i$$

$$H(X) = -\sum_x p(x) \ln p(x)$$

$$H(Y) = -\sum p_i \log_2 p_i$$

$$H(Y) = -\sum_y p(y) \ln p(y)$$

Where,  $H(X, Y)$  is the joint entropy of X, Y

$$MI(X, Y) = \sum_{x,y} p(x, y) \ln \frac{p(x, y)}{p(x)p(y)} \quad (2.4)$$

Normalized mutual information (NMI) is often used these days and it is used to overcome the overlapping problem of images, it has less sensitive to overlap changes. Mathematically, it is described mathematically as

$$NMI(X, Y) = H(X) + H(Y) / H(X, Y) \quad (2.5)$$

$$NMI(X, Y) = \frac{\sum_{x,y} p(x, y) \ln \frac{p(x, y)}{p(x)p(y)}}{-\sum_{x,y} p(x, y) \ln p(x, y)} \quad (2.6)$$

## 2.3 Optimization Techniques

### 2.3.1 Introduction

Optimization is the process of selecting best particle among the group of particles and there are different types of optimization techniques, among that one class of optimization is called Classical optimization. These techniques are used for verifying the optimum solution and these are used for maximizing or minimizing the cost function [24]. Classical optimization techniques are inquisitive or analytical methods and uses differential calculus in pointing the optimum solution and scope is limited in case of practical applications. Among that few of them include objective functions which aren't differentiable and/or continuous. In optimization problems for development of most of the numerical techniques, classical techniques are used. They are develop gradually into advance techniques and more suitable in solving practical problems coming across these days. These methods undertake the cost function was twice differentiable and w.r.t the derivatives, design variables and are differentiable or continuous.

The functions which can vary w.r.t Single variables, multivariable without any limitations, multi functions, inequality and equality are the main issues that can be handled by the classical optimization techniques.

The second classification type of optimization is numerical methods of optimization. In this, linear programming studies, if the objective function or cost function is linear and the set design variable space and it is specified using only linear equalities and inequalities. In quadratic programming, when the design variable set must be specified with linear equalities and inequalities then it allows the objective function to have quadratic terms. In nonlinear programming the objective function or the constraints or both contain nonlinear parts. In stochastic programming case, constraints depend on random variables. In a dynamic programming case, in which the optimization strategy is based on splitting the problem into smaller sub-problems.

The third classification type of optimization is called advanced optimization techniques. These are also known as hill climbing techniques. Hill climbing is also known as graph search algorithm., first closer node is selected in In simple hill climbing and in steepest ascent hill climbing matched all successors and the closest to the solution is selected and both forms fail if there is no closer node. If there are local maxima this may happen in the search space which are not solutions and it is used widely in artificial intelligence fields.

The fourth classifying type of optimization is simulated annealing. The name itself name came from annealing process in metallurgy, from a technique which involves heating and controlled cooling of materials to rise the size of the crystals and reduce the defects. Every point in the search space is compared and the cost function is minimized in this state. Eventually the goal is to carry the system, from some random initial state, to the state with minimum possible energy.

The fifth classification type of optimization is called ant colony optimization technique. In this method, ants solve optimisation problems indirectly communicate interaction via environment directions to each other. Ants are behaviourally unpretentious, but they can perform complex tasks. Ants travel in both directions forward path and backward path and pheromones have to evaporate. An ant's path represents a specific candidate solution and they can communicate using pheromones.

For avoiding the local optimum pheromone evaporation techniques are used and convergence at a local optimal solution is verified. In these paths which was chosen by the first ants will tend to be extremely attractive to the succeeding ones and the survey of study of the solution space would be restricted. Thus, when an ant catches the trove to the shortest path from the colony to the food source, other ants also generally follow the same path.

### **2.3.2 Genetic Algorithm**

A genetic algorithm (GA) is a local search optimization technique used to find optimum solutions to search problems [11]. Genetic algorithms are good at optimizing techniques with many local optimum points and it is a population based and completes random based technique and occurs in generations. GA's are computational models of natural evolution in which stronger individuals are tends to survive and weaker individuals are die out. GA's are a stochastic method and a good behavior in learning of parameters [23]. Genetic algorithms differ substantially from more traditional search and optimization methods. The most significant differences are:

- GA searches not only a single point but the search goes on through all the points in parallel, and the work emphasizes more on parameter set compared to parameter.
- GA doesn't require auxiliary knowledge or derivative information; the search is influenced only with fitness levels and respective objective function
- The search in GA is through probabilistic transition rules, but not deterministic.
- Since no definite objective function exist, GA in general more direct approach to apply.
- For a given problem, GA can provide various potential solutions.

In GA Initialization, Reproduction (cross over & mutation), Termination criterion are the three basic parameters these are inspired from evolutionary of biology. Genetic algorithms are used for maximization and minimization problems.

In each generation, the cost value of the population is calculated, from fitness function individuals are selected randomly, and modified by using mutation to form a new population. For the next iteration of the algorithm the new population is used. GA's are also used to enhance image contrast and it is done by mapping of image values. The basic blocks of genetic algorithm are shown in figure 2. 2.



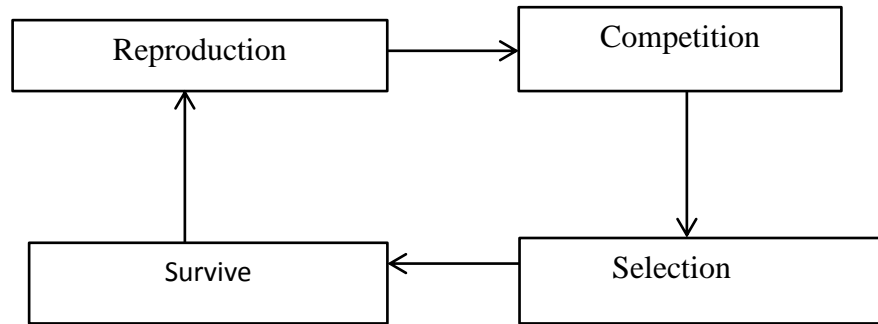


Figure 2.2: Basic Operators of Genetic Algorithm

- **Reproduction-** Reproduction is the first genetic operator applied on population. Child parameters (chromosomes) are selected from the population of parents to cross over to produce offspring. It is based on the Darwin's evolution of survival of the fittest. Therefore this operator is known as selection operator. The various methods of selecting chromosomes for parents to cross over are
  1. Roulette-Wheel Selection
  2. Tournament based Selection
  3. Rank based selection
  4. Boltzmann selection
  5. Elitism
- **Cross over-** After reproduction phase, population is improving with better individuals. It makes good strings but does not create new population. Cross over operator is applied to the mating pool with a hope that it would create better strings. Generally the cross-over probability range varies from 0.5 to 1.
- **Mutation-** after cross over mutation operation is performed and mutation of a bit involves in flipping changes 0 to 1 and vice versa. Mutation probability  $P_m$ , varies from 0.01 to 0.5.

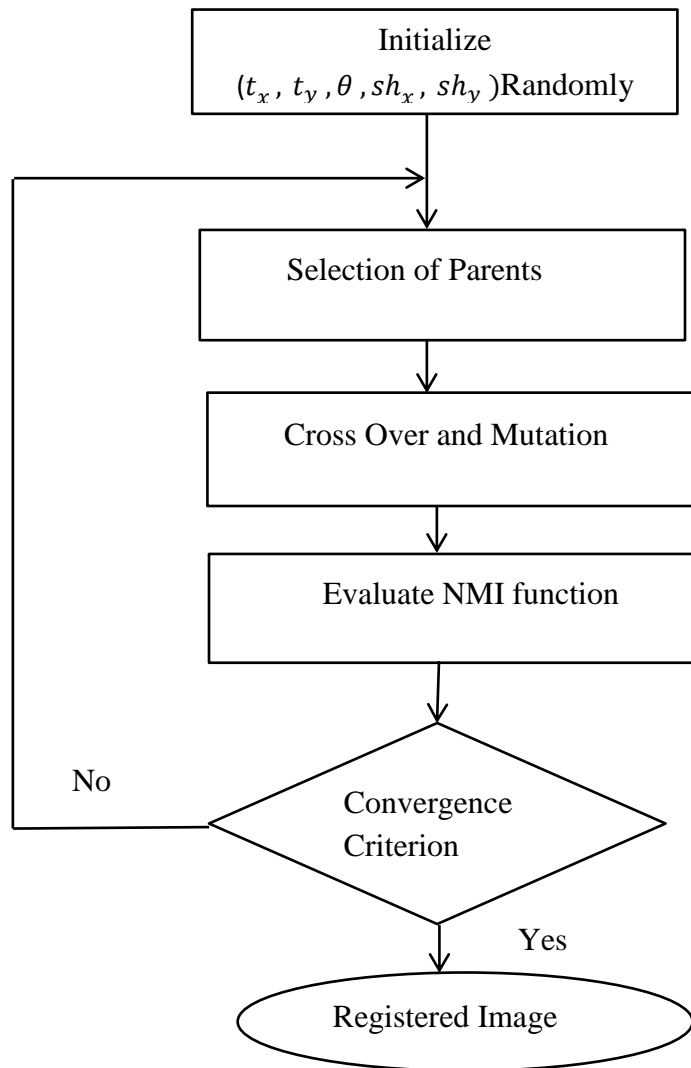


Figure 2.3: flow diagram of GA

Required steps for implementation of genetic algorithm are

**Step1:** initialize size of a population, cross over probability ( $p_e$ ) and the mutation probability( $p_m$ ).

**Step2:** Define a fitness/cost function to measure the cost of an individual chromosome in the given problem statement.

**Step3:** Randomly generate an initial population of chromosome of size  $N$ ;  
 $x_1, x_2, x_3, \dots, x_N$ .

**Step4:** Calculate the fitness of each chromosome individually.

$f(x_1), f(x_2), f(x_3), \dots, f(x_N)$ .

**Step5:** Select a pair of chromosomes from the current population and the parent chromosomes are selected.

**Step6:** By applying the genetic operators, cross over and mutation create a pair of offspring chromosomes.

**Step7:** Place the new offspring chromosomes in the new population.

**Step8:** Repeat step5 until the population size becomes equals to the size of the initial populatio.

**Step9:** Replace with new offspring population instead the initial chromosome population

**Step10:** repeat step4 the process until it satisfies the termination criterion.

Issues of genetic algorithm are reproduction, population size, mutation rate, selection process, crossover, termination criterion, scalability. Some of the benefits of genetic algorithm are easy to understand, it supports multi objective optimization, it is good for noisy environment, inherently parallel and easily distributed, flexible to form building blocks of hybrid optimization problems.

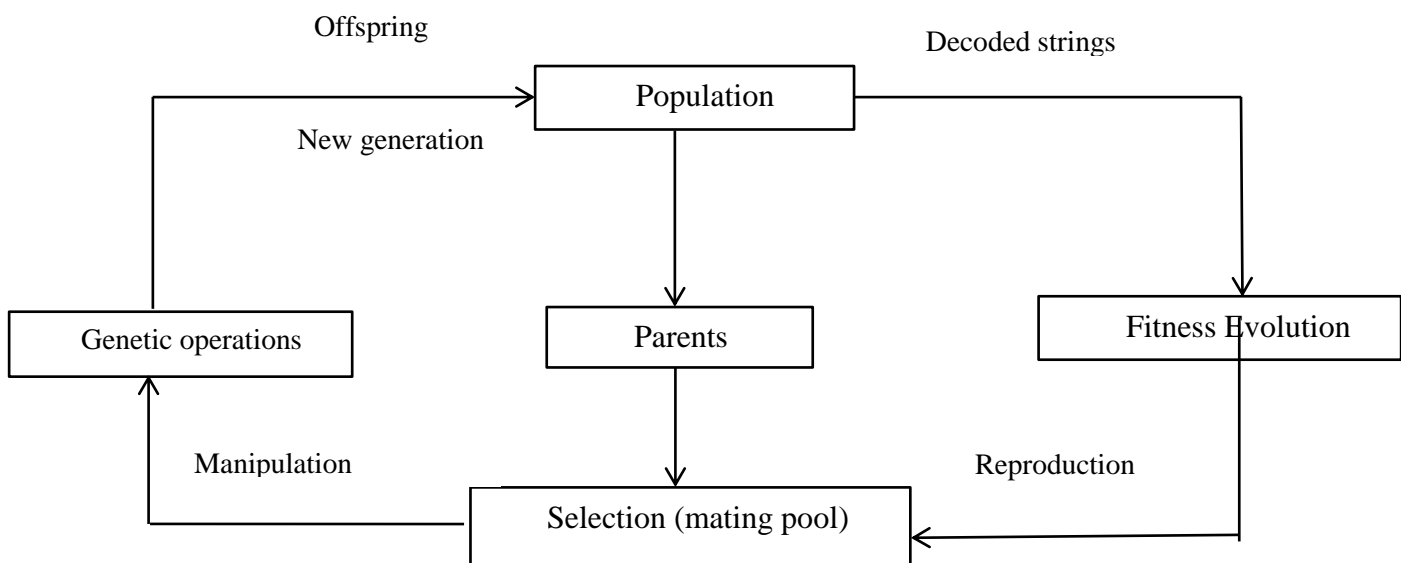


Figure 2.4: GA Cycle of Reproduction

Implementation of the genetic algorithm is complex and it is completely random based optimization technique. Due to this, results are not much accurate. In order to overcome these problems other advanced optimization techniques are applied further.

### 2.3.3 Particle Swarm Optimization (PSO)

Particle swarm optimization is robust and based on intelligence of swarms it is a stochastic optimization technique. It was developed by James Kennedy and Russell Eberhart in 1995 inspired by social behavior of bird flocking or bird fishing. PSO is a global optimization population based evolutionary algorithm for finding out the best particles.

PSO is initialized with transformation parameters randomly and then searches for best transformation by updating parameters. Particles are evaluated according to cost function i.e. NMI in each step. In every criterion, each particle is updated by two best solutions. *pbest* is the first fitness solution, which has achieved so far (the fitness value is also stored) this is also called as local best solution. *gbest* is the best solution value, that is tracked by the swarm of particle optimizer is the best value obtained so far by any particle in the population and this second best value is

Each particle modifies its current position and velocity according to *pbest* and *gbest* by the distance between its current positions. Particles are update by the eqn. 5 &6.

$$v_{id}^{k+1} = w * v_{id}^k * c_1 * r_1^k * (pbest_{id}^k - x_{id}^k) + c_2 * r_2^k * (gbest_{id}^k - x_{id}^k) \quad (2.7)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (2.8)$$

Where,

$i$  = Particle index

$k$  = Discrete time index

$v_i$  = Velocity of  $i$ th particle

$x_i$  = Position of  $i$ th particle

$p_i$  = Personal best position found by the  $i$ th particle.

$g_{best}$  = Global best position found by swarm

Working process of Particle swarm optimization algorithm is described below.

**For** each particle

    Initialization of each particle with random number

**End**

**Do**

    Evaluate the cost/fitness function for each particle

    If the cost/fitness value is better than pbest value then set new value as the current pbest.

**End**

    Choose the particle with the best cost/fitness value and assign as the gbest

**For** each particle

    Evaluate particle velocity using eqn (2.7) velocity update equation

    Update particle position using eqn(2.8) position update equation

**End**

Working principle of particle swarm optimization shown in below flow chart.

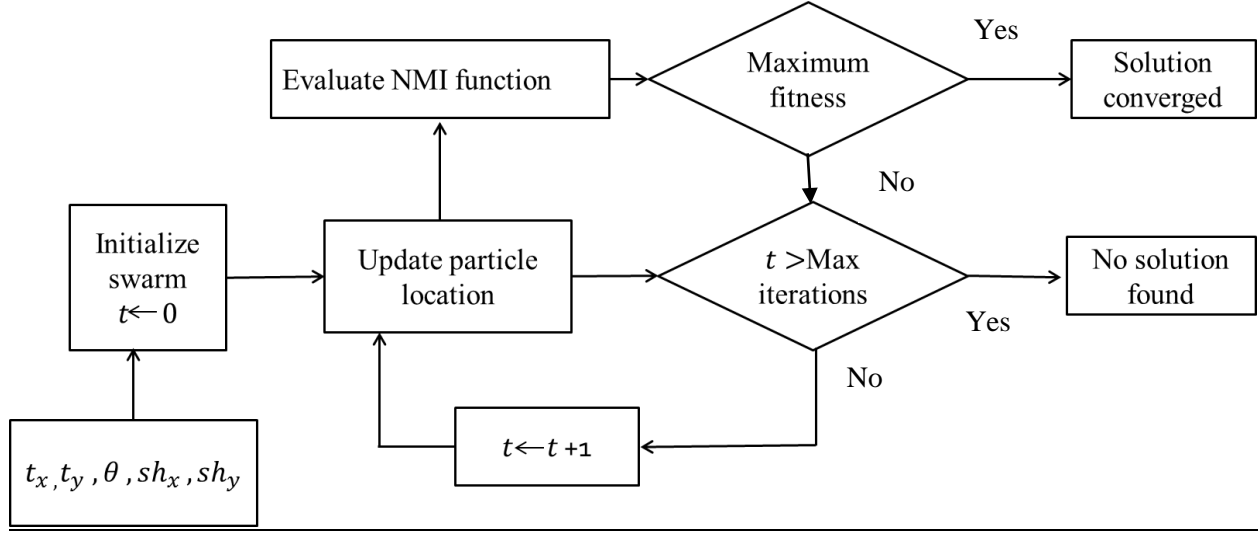


Figure 2.5: Flow chart for particle swarm optimization

Figure 2.9 shows a more detailed flow diagram of image registration using PSO. The PSO process for image registration works as follows. During initialization, a fixed number of swarm particles  $[t_x, t_y, \theta]^T$  are randomly placed. In each iteration, the positions of the particles are updated according to Eqn.(2.7) and eqn.(2.8), then the objective function NMI is evaluated at the location of every swarm particle and the individual best and swarm best are updated using velocity and position eqns. The swarm best is compared with the goal. If it is reached maximum fitness then we can consider it as registration is completed and two images are aligned perfectly but in another case increase the swarm size and again go for updating of the particles until a preset number of iteration has been reached, in which case we consider the PSO not converging and the registration has failed [13].

Particle swarm can be used for maximization or minimization of the objective or cost function when two images are registered or aligned. There are many different techniques based on image similarity, such as (normalized) cross-correlation, sum of squared difference (SSD), or one based on mutual information, normalized mutual information for images from different sensor modalities. These techniques would be sufficient for demonstrating the effectiveness of PSO for registration, normalized mutual information of the two images have been implemented for its simplicity, the result becomes independent of the size of overlap (only overlapping areas are used for computing the difference) of the two images.

Application of particle swarm optimization are function optimization, artificial neural network training, Image processing applications, PSO is also implemented areas where GA can be implemented, optimization of power distribution networks, structural optimization, processing of bio-chemistry, system identification in biomechanics etc. Advantages of particle swarm optimization are easy to implement, computation process, derivative free algorithm, very few algorithm parameters and it is very efficient global search algorithm.

The drawbacks of PSO are that the swarm may converge prematurely and to face the problem of classification of instances in databases it has been used. Weak local search ability is the main problem in PSO due to this problem PSO is performed unsatisfactorily. The trade-off between local search and global search is necessary for the performance of the algorithm. Hence, to increase the convergence speed of the particles in order to achieve a better balance between local search and global search.

## CHAPTER3

# RIGID IMAGE REGISTRATION OF SATELLITE IMAGES USING PROPOSED GA-PSO ALGORITHM

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Rigid type of transformations is used to register images of the same image. For rigid registration, the spatial transformation is described by a set of parameters. Translation and rotation are the parameters of rigid registration problem. In two dimensions, rigid registration requires four parameters: two translations and two rotations. Transformation is estimated by using translation, rotation parameters. Mathematically, Geometrical transformations that maps the points from one spatial coordinate (x,y) to the other spatial coordinate (u,v) can be written as  $(u,v) = T\{(x,y)\}$  where T is the transformation.

The set of transformations classified as two categories they are rigid transformation and non- rigid transformation and each transformation divided into many sub transformations they are projective, affine, similarity, Euclidean.

### 3.1 Rigid Transformations

Rigid is a one class of transformation and it is defined as geometrical that does not alter the size and shape of the image. Rigid transformations are simple and easy to specify, and there are various approaches towards it. Translation and rotation are two parts to the spec in each method.

Mathematically, rigid transformation can be represented as

$$(u, v) = (x, y) * R + t$$

where R is a 2x2 orthogonal rotation matrix and t is a two-dimensional translation vector. A rigid transformation has 4 degrees of freedom (DOF): 2 from translation and 2 from rotation. The rigid transformation is shown in fig 3.1.

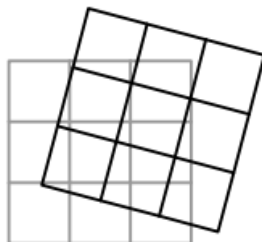




Figure 3.1: Rigid transformation

### 3.1.1 Translation

Transformation can be two dimensional vectors or three dimensional vectors. In this work two dimensional images have been used. Translation is one of the parameter in rigid transformation. It can be defined as how much amount of information or points or parallel shift of a figure moving from one position to the other with respect to the x,y coordinate system. Translation of the two dimensional vector  $t$  specified by two-dimensional  $t_x, t_y$  are relative to a set of x,y cartesian axis. For three dimensional vector,  $t_x, t_y, t_z$  are relative to a set of x,y,z cartesian axis. Translation occurs due to different orientation of the sensor. Mathematically, the translation of point  $P=[x \ y]^T$  can be represented as by a vector  $T=[t_x \ t_y]^T$  is given by

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix} = \begin{bmatrix} x + t_x \\ y + t_y \end{bmatrix} \quad (3.1)$$

Diagrammatically translation along x & y axis are shown in fig.3.1.1

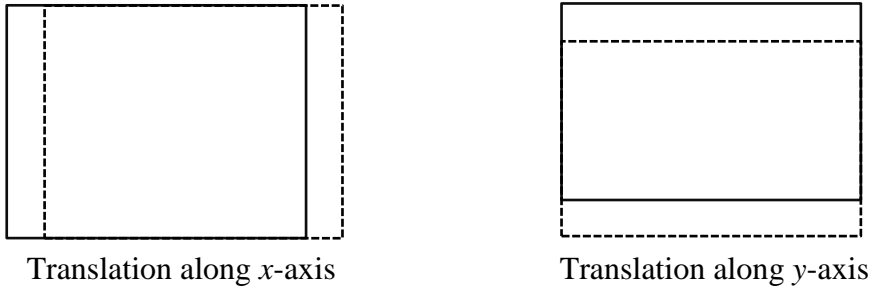


Figure 3.2: Representation of translation along x,y axis

### 3.1.2 Rotation

Rotation is measured by degrees and defined as how much angle of the image is rotated and the rotation of the image is or angles and its rotation is specified as a single value in two dimensions. In a two dimensional plane Consider a point at co-ordinate  $(x_1, x_2)$ . New co-ordinates  $(y_1, y_2)$  rotation of this point, by  $\theta$  radians around the origin, can be generated by the transformation: mathematically, rotation can be represented as,

$$\begin{aligned} y_1 &= \cos(\theta) x_1 + \sin(\theta) x_2 \\ y_2 &= -\sin(\theta) x_1 + \cos(\theta) x_2 \end{aligned} \quad (3.2)$$

Diagrammatic representation of the rotation will be shown in fig.3.1.2

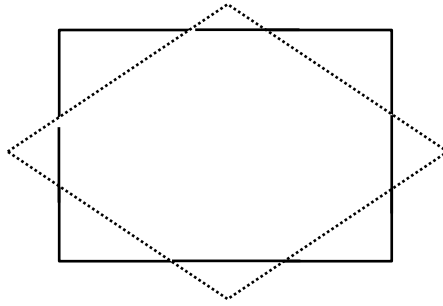


Figure 3.3: Representation of Rotation

### 3.2 Affine Transformation

Affine transformation is also one class of mapping and it represents the relation between two images. Affine transformation is a combination of translation, rotation, along with scaling and or shear components. In affine transformation no longer to maintain the properties of lengths. parallel lines in the original image remain parallel after transformation mathematically affine transformation can be represented as

$$[u, v] = [x, y] * A + t \quad (3.3)$$

where A is a matrix. there is no restriction of the matrix A. diagrammatically affine transformation can be represented as

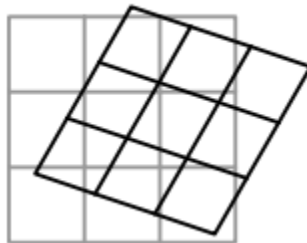


Figure 3.4. Affine transformation

Affine transformations are more distortions than rigid transformations and more general than rigid transformations. Mathematically, 2D affine transformation can be expressed as

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} t_x \\ t_y \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{13} & a_{14} \end{bmatrix} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad (3.4)$$

where  $(x_2, y_2)$  represents the new transformed coordinate of  $(x_1, y_1)$  the matrix  $\begin{bmatrix} a_{11} & a_{12} \\ a_{13} & a_{14} \end{bmatrix}$  can be any transformation scaling and shearing.

### 3.2.1 Scaling

Scaling is a transformation and it is used to enlarge or diminishes the objects. Due to scaling transform does effects the change in altitude of the sensor. The point  $P=(x,y)$  changes due to scaling by a constant factor  $s$ :

$$x' = sx$$

$$y' = sy$$

Mathematically, A two dimensional scaling transformation can be represented as,

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

where,  $s_x$  represents the scaling along x-axis

$s_y$  represents the scaling along y-axis

Diagrammatically, scaling transformation is shown in fig

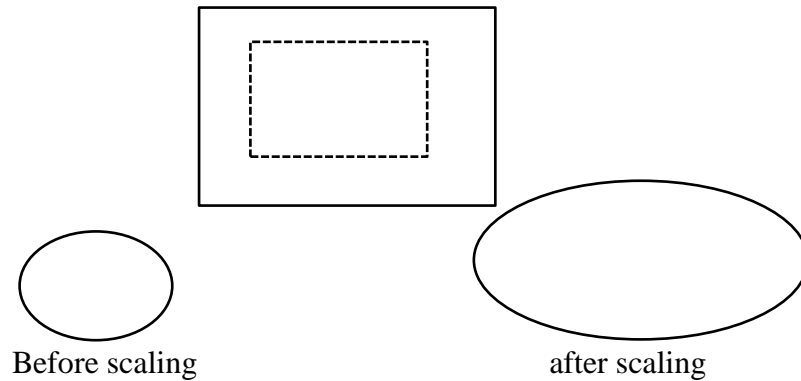


Figure 3.5: Representation of scaling

### 3.2.2 Shearing

Shear is a transformation but it is not a parameter in rigid transformation, it is a non-rigid transformation. Shearing in both directions are same. In 2-D shearing x shifting and y-shifting done by using memory shift. X-shear can be done by row memory shifting, but y-shear cannot be done. Mathematically, in matrix form shearing can be represented as,

$$sh_x = \begin{bmatrix} 1 & a \\ 0 & 1 \end{bmatrix} \quad sh_y = \begin{bmatrix} 1 & a \\ 0 & 1 \end{bmatrix}$$

where,  $sh_x$  = shearing along x-axis

$sh_y$  = shearing along y-axis

Diagrammatically shearing can be represented as

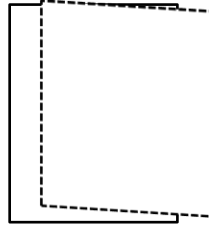


Figure 3.6 Representation of Shearing

### 3.3 Optimization Technique: proposed hybrid GA-PSO Algorithm

Hybrid GA-PSO algorithms were proposed to overcome the limitations of PSO. In this thesis, hybrid GA-PSO optimization technique have been proposed and which incorporates the notion of Genetic Algorithm, Sub-population, and Cross-over into the PSO. In this proposed algorithm the particles are grouped into the M number of sub-populations, each of them has its own global best particle  $gbest_{sub,m}$ , for  $m=1,2,\dots,M$ . GA and PSO both work with the same initial population. GA is simple over PSO. It is the main advantage of PSO and algorithmic, another difference between PSO and GA is that controllability of its convergence. For convergence of GA Mutation, Crossover rates can affect, but these cannot be comparable to the manipulating of the inertia weight. In fact, the swarm's convergence decreases and inertia weight dramatically increases. PSO converges before convergence criteria it is the main problem of PSO. To stable point, which is not necessarily maximum. To prevent this problem, velocity, position is updated. Through notion of crossover, mutation the position update is done hybrid. Information can be exchanged between particles by applying crossover operation, to have the ability to move to the new search area. To increase the population of diversity and to avoid the local maxima mutation operation is applied.

Steps for implementation of hybrid GA-PSO algorithm

**Step1:** Initialization: Generate population size randomly.

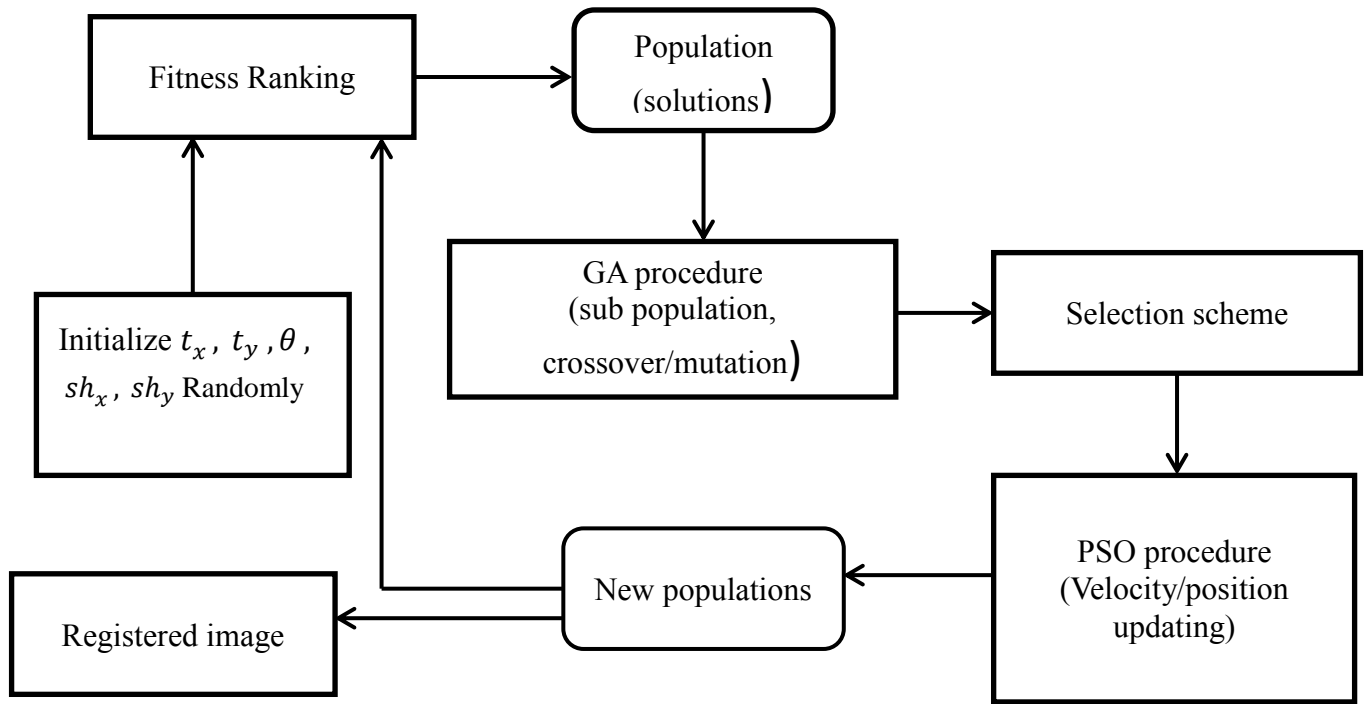
**Step2:** Evolution & ranking: Evaluate the fitness of each particle individually and assign rank on the basis of the fitness values.

**Step3:** GA operators cross over and mutation to the particles and generates new population

3.1 Selection- from the population selects the individuals according to fitness function

3.2 crossover- using best individuals, update the individuals by applying two- parent crossover

Figure 3.7 : Flow chart for proposed hybrid GA-PSO algorithm



3.3 mutation- according to the equation below, apply mutation to the best updated chromosomes

$$x'_k = x_k + rand * N(0,1)$$

**Step4:** PSO method- Apply PSO operator's velocity and position updates for updating the individuals with worst fitness.

$$v_{id}^{k+1} = w * v_{id}^k * c_1 * r_1^k * (pbest_{id}^k - x_{id}^k) + c_2 * r_2^k * (gbest_{id}^k - x_{id}^k) \quad (5)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (6)$$

Where  $c_1 = c_2 = 2$  and  $w = [0.5 + rand/2.0]$  eqn illustrates that the new velocity for each individual, from previous velocity particle is updated.

Eqn.(5) shows how each particles position is updated during search in the solution space until the termination criterion is reached.

## CHAPTER 4

### RESULTS AND ANALYSIS

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In this work of satellite image registration, NMI is used as the similarity metric and to maximize the similarity metric between the reference and the floating image several evolutionary algorithms such as GA, PSO and hybrid GA-PSO are implemented. Intensity based techniques are applied to register satellite images and NMI is very general and powerful and can be applied automatically without prior segmentation on a large variety of data and as well works better for overlapped images as compared to MI. In order to maximize the NMI, hybrid GA-PSO is implemented in order to overcome the limitations of GA and PSO. The random initialization and computational complexity makes GA oppressive, whereas weak local search ability with a premature convergence is the main drawback of PSO. Hybrid GA-PSO makes a trade-off between the local and global search in order to achieve a better balance between convergence speed and computational complexity.

#### 4.1 Mis-registration Calculation

A mathematical framework has been developed for optimizing the errors in registration by estimating the parameters (translations, rotations, and scale). Mis-registration occurs when two images are not matched perfectly and images from different individuals typically cannot be

aligned accurately. It is calculated to find out the percentage of mismatch between reference and floating images. Mathematically it can be defined as

$$MRE (\%) = \frac{Reference\ image - Floating\ image}{Reference\ image} * 100$$

## 4.2 Structural Similarity Index(SSIM)

Structural similarity index is the objective image quality metric between the reference and test image. Concept of structural similarity metric defines the structural information. The index is defined based on three physical parameters such as luminance, contrast and structure. The physical parameter are defined statistically in terms of mean, variance and covariance. Mathematically, SSIM of the reference and test image is defined as

$$SSIM(x, y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad (4.2)$$

where,

$\mu_x, \mu_y$ = mean variance of the reference and test image

$\sigma_{xy}$ = covariance of the reference and test image

C1, C2 are constants;

$C1 = (0.01 * L)^2$ ;  $C2 = (0.03 * L)^2$ ;

L refers to dynamic range (255 for gray scale)

To validate the proposed work, registrations were performed for a set of satellite images. From the various convergence plot, it is observed that GA converges after 18 iterations, PSO converges after 25 iterations whereas hybrid GA-PSO converges after 15 iterations with 23 sec. From the similarity index tabulation, it is observed that the MI and NMI values for hybrid GA-PSO significantly increases as compared to GA and PSO for both rigid and affine transformation. For Fig. 4.2, the MI value for GA and PSO are 0.746 and 0.831 respectively and 0.918 for hybrid GA-PSO. Likewise the NMI value for GA and PSO are 0.882 and 0.898 respectively and 0.964 for hybrid GA-PSO in rigid registration. For Fig. 4.4, the MI value for GA and PSO are 0.826 and 0.874 respectively and 0.938 for hybrid GA-PSO. Likewise the NMI value for GA and PSO are 0.896 and 0.918 respectively and 0.97 for hybrid GA-PSO in affine registration. SSIM index is more close to 1 in GA-PSO as compared to GA and PSO shows the

case of perfect registration without loss of generality is tabulated in Table 4.2. Percentage of mis-registration error is approximately 6-7% less for hybrid GA-PSO than that of GA and 4-5% less as compared to PSO.

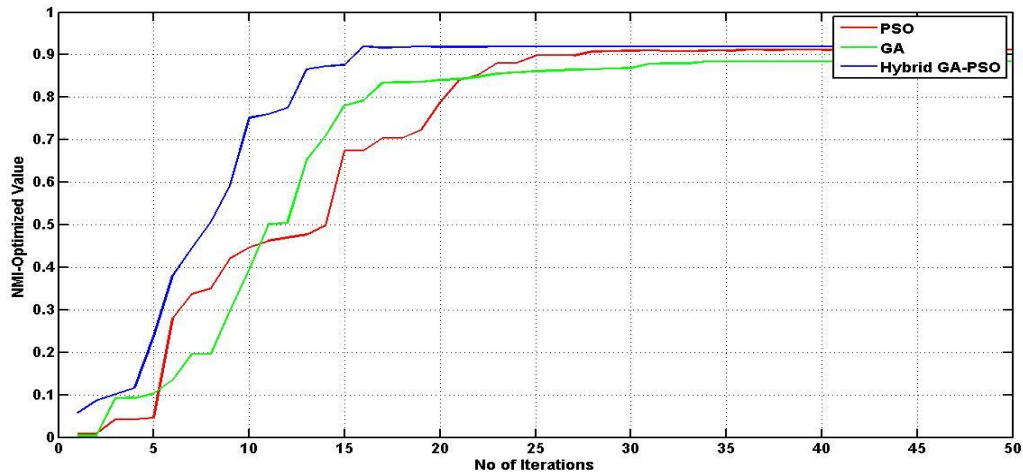
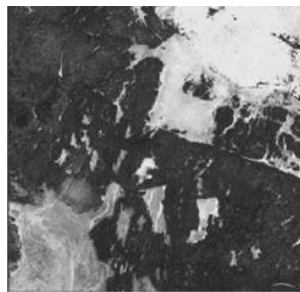
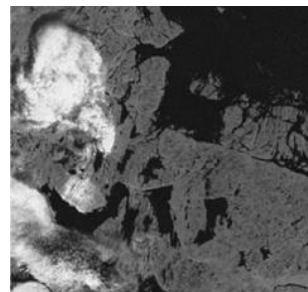


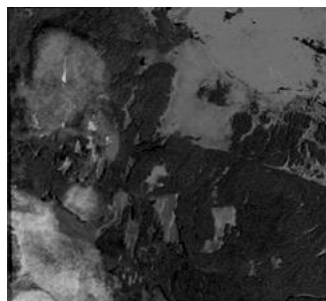
Figure 4.1 Rigid Image Registration plot using NMI



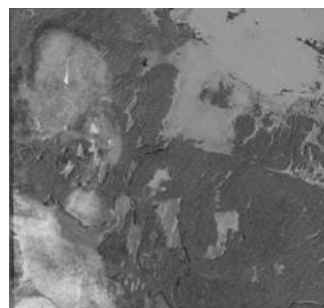
(A) Reference Image



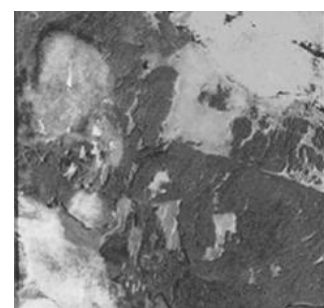
(B) Floating Image



(C) Registered Image using GA



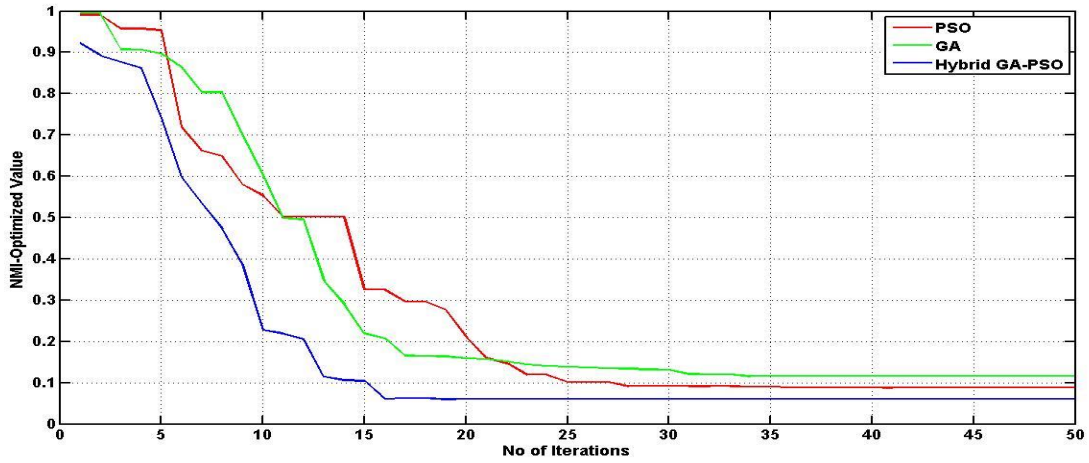
(D) Registered Image using PSO



(E) Registered Image using hybrid GA-PSO



Figure 4.2 Rigid Image Registration plot using NMI



The comparative analysis was performed between hybrid GA-PSO with GA and PSO, to measure the performance efficiency. The images for testing were taken from SAR database. The parameters considered for analysis are MI, NMI and SSIM, & along with that error computation was also made. Observing the results it is clear that, for hybrid GA-PSO the values obtained for MI, NMI and SSIM are considerably good than the existing algorithms. This ensures that the proposed algorithm extract more information and the error rate is less. From the iterative comparison graphs, we can conclude that the proposed algorithm takes same number of iterations as GA and PSO with a much better performance.

## **CONCLUSION**

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In Image registration, the intensity based technique is applied to the satellite images for registration problem. Rigid, affine registration schemes are proposed by optimizing the normalized mutual information as similarity measure. This similarity measure produces better accurate registration results for satellite images that have been tested. To determine corresponding better optimum values evolutionary techniques, like genetic algorithm, PSO algorithm and hybrid GA–PSO algorithm are applied, and compared based on normalized mutual information, translation, rotation scaling and shearing parameters. In this thesis, the maximum amount of normalized mutual information is determined using the hybrid GA- PSO optimization technique and the corresponding optimized registration parameters are determined.

## **FUTURE SCOPE**

- This work can be extended to 3D non rigid registration techniques.
- Feature based methods can be implemented
- Using other optimization techniques can be implemented in order to get better optimum values and to determine optimized registration parameters.

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